

A Method for the Detection and Classification of Irregularities in a Civil Structure

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Abstract— The proposed system discloses a method for the detection and classification of irregularities in civil structures. The system comprises a repository that stores a dataset of civil structures, predefined features, a set of classification rules, and a set of rules; an input unit receives an image of civil structure; a retrieving and pre-processing unit retrieves an image and generates at least one pre-processed image; an extraction unit extract feature; a crawler and extractor unit crawl and matches extracted features with predefined features; an object detection and removal unit detect one-or-more objects from pre-processed images and remove unwanted, overlapped objects and generate enhanced pre-processed image; a processing unit generates processed image; an identification unit identifies region; a classification unit receives the processed image and matched extracted features from crawler and extractor unit detects and classify irregularity from the region and generate a notification and display notification.

Index Terms— Irregularity/ Irregularities, set of classification rules, a set of predefined features;

I. INTRODUCTION

Identification and detection of irregularities in civil infrastructure is a crucial and tedious task. It is not an easy task to cover all regional areas for finding irregularity attempts. Most government authorities from various cities are hired a third party to find irregularity attempts. The third-party agent takes a survey and evaluates the structure if any irregularity is attempted or not. Then submit the report to the authority. Irregularities are categorized into two types “Irregularity in public” and “Irregularity of civil structures”.

Irregularity is in public: The person who has encroached upon government land or public property.

Irregularities of civil structures: The irregularities in civil structures like damage to concrete surfaces, wall inclined, bends in pillars, and cracks in the civil structures.

Governing bodies do this by tracking and monitoring the irregularities activity half-yearly or once in early detection of irregularities in both scenarios.

Any encroachment of civil infrastructure is detected by the manual process which is carried out by the human. Due to this human intervention, the process execution requires more time. This process does not provide regular synchronous data and sometimes leads to false data because data is dependent on another process. The main motivation is to detect the change in encroachment in any images where traditional methods are very time-consuming. For this, need to provide a robust solution with the integration of recent technology trends.

The method is designed to enhance the overall efficiency of structural assessment, providing engineers and inspectors with a comprehensive tool for early detection of potential issues. With real-time monitoring capabilities,

this method contributes to proactive maintenance strategies, ultimately ensuring the safety and longevity of civil structures by addressing irregularities in their early stages, before they escalate into more severe problems. This innovative approach holds promise for advancing the reliability and resilience of civil infrastructure across diverse applications, from buildings and bridges to dams and other critical structures.

II. REVIEW LITERATURE

Conventionally, tracking and monitoring civil structures for irregularities is a tedious task. For finding and detection of irregularities are done manually and require operator involvement. The governing bodies will hire a third party or form a team of operators and specialists for the inspection of civil structures sites. This team of operator and specialists need to visit the site physically and inspect civil structures. After inspection, the team of operators prepares and submits the report for the examined civil structures. A manual examination may lead to a possibility of error or/and manipulation in reports.

All these monitoring and detection of irregularities are human-operated and hence there are some possibilities of error. However, this is a time-consuming, inefficient, and static task. Also due to the human intervention involved, the accuracy of such a tracking system is highly questionable.

Cracks in the concrete surface are one of the first indications of structural damage, which is crucial for maintenance and will cause serious environmental damage if left unsupervised. The most widely used approach for crack examination is manual inspection. In a manual examination, a schematic of the crack is produced manually, and the irregular conditions are documented. The manual approach lacks impartiality in the quantitative analysis since it is dependent entirely on the specialist's knowledge and experience.

Irregularities in civil structures lead to a hazardous situation and it is difficult to trace or find the reason behind this. To prevent and avoid hazardous situations or conditions, civil structures need to be inspected and tracked regularly.

Authors Chia-Hung Yeh, Chih-Hsiang Huang, Li-Wei Kang discussed the methodology of deep learning-based architecture using multi-scale residual learning (MSRL) and the Image decomposition method [1]. It extracts images in structure and features where the result of the image is given to the next layer. The challenge observed in this method is, that the images are degraded by complex media such as smoke, fog, rain, and snow. [1]

Authors Faqiang Wang; Haiyang Huang; Jun Liu, performed the traditional model based variational methods and deep learning based algorithms. It proposed a noise removal problem. Authors perform the regularization, synthesis, parameters estimation, and noise classification in four steps with the operator splitting scheme methods for noise removal. The challenges are found in image reconstruction and inverse problems of images which consist of complex background or mixed images. [2]

Authors Liqiong Lu, Yaohua Yi, Faliang Huang, Kaili Wang, Qi Wang discussed a methodology using a combination of Local CNN (LCNN) & Global CNN (GCNN) which are based on ResNet-20 for script identification of images. Adaboost algorithm is used where it combines the result generated by LCNN & GCNN. The method is identifying various languages from scene images located in nature. These methods faced various challenges:

- 1) Identification where text and background are mixed.
- 2) Sometimes it complex background is used.
- 3) Poor quality of text not identified.
- 4) Large text spacing or non-horizontal text.
- 5) Shelters in front of the text.

Authors Manuel López-Antequera, María Leyva Vallina, Nicola Strisciuglio, Nicolai Petkov,(2019) discussed a method to identify various place recognition using CNN and classifiers. Where they performed on MNIST data set, garden data set, and butterfly data set. The feature extractor was not fine-tuned for the task. [4]

Authors Shiqing Zhang, Xianzhang Pan, Yueli Cui, Xiaoming Zhao, Limei Liu (2019) discussed the method of facial expression recognition (FER) to extract facial recognition using a hybrid deep learning model. It performed this method on video segments. The challenge is to develop real-time FER based on CNN to extract facial expressions. [5]

Authors Jongyoo Kim, Anh-Duc Nguyen, Sanghoon Lee discussed the method of deep image quality assessor (DIQA) to separate the training of NR-IQA into two stages:

- 1) An objective distortion part.
- 2) Human visual system-related part

Where CNN performs learning in two stages where first is to predict the objective error map of a given set of images, and then predict the subjective score. It senses to visualize and analyze the learned perceptual error maps but sensitivity maps that can provide a more interpretable analysis. [6]

Authors Yutan Wang, Yingpeng Dai, Xiangnan Liu, Bohan Liu, Xiaoyun Guo discussed the method of combining quadratic optimization with variable window processing. To enhance image quality, optimal channel processing is done. Then noise reduction in each channel will be selected automatically by the optimal algorithm. The image quality will affect different filtering processes like mean filtering, median filtering, and adaptive filtering. [6]

Authors Hailiang Li, Yongqian Huang, and Zhijun Zhang, discussed an R-CNN Method to extract the same objects in a different scene, the challenge is to improve the efficiency of the Faster R-CNN method during testing which leads to less time required for fine-tuning during training. [7].

Authors Florin C. Ghesu, Edward Krubasik, Bogdan Georgescu, Vivek Singh, Yefeng Zheng, Joachim Hornegger, Dorin Comaniciu discussed the Marginal Space Deep Learning (MSDL) method to exploit both the strengths of efficient object parameterization in hierarchical marginal spaces and the automated feature design of Deep Learning (DL) network architectures. It detects and segments the aortic valve in ultrasound using an extensive dataset of 2891 volumes from 869 patients, showing significant improvements of up to 45.2% over the current methods. There are two challenges found, [8]

- 1) Efficiency in processing a large volume of input images.
- 2) Need for strong image features that are representative.

III. METHODOLOGY

Pre-processing

The dataset utilized for this implementation is sourced from Mendeley data, titled "Concrete Crack Images for Classification." This dataset comprises 40,000 images, each measuring 227 x 227 pixels and containing RGB channels. The images are obtained from Concrete Crack Images for Classification - Mendeley Data. This dataset specifically focuses on concrete images exhibiting cracks.

The dataset is categorized into negative and positive crack images, totaling 20,000 images per class, thus summing up to the overall 40,000 images. Each image maintains a resolution of 227 x 227 pixels with RGB channels. These images originate from 458 high-resolution pictures (4032x3024 pixels) using the methodology proposed by Zhang et al. It's important to note that the high-resolution images exhibit variations in surface finish and illumination conditions. Notably, no data augmentation techniques, such as random rotation or flipping, have been applied to the dataset.

- Dataset for implementation is Concrete Crack Images for Classification from Mendeley data, which contains 40000 images with 227 x 227 pixels with RGB channels.
- The dataset contains concrete images having cracks.
- The dataset is divided into two as negative and positive crack images for image classification.
- Each class has 20000 images with a total of 40000 images with 227 x 227 pixels with RGB channels.
- The dataset is generated from 458 high-resolution images (4032x3024 pixel) with the method proposed by Zhang et al.
- High-resolution images have variance in terms of surface finish and illumination conditions.
- No data augmentation in terms of random rotation or flipping is applied.

B. Proposed Methodology

The manual detection of irregularities in civil infrastructure relies on human operators or teams, leading to a time-consuming process. Human intervention in this process results in prolonged execution and lacks regular data synchronization, occasionally resulting in inaccurate data. The primary goal is to identify irregularities in images, a task where traditional methods prove to be exceedingly time-consuming. Detecting changes in civil structures and pinpointing specific alterations indicating irregularities in infrastructure is particularly challenging.

The detection and classification of cracks are crucial for assessing their severity. Crack detection involves recognizing the presence of a crack, while crack classification categorizes the crack based on extracted features from the crack region. Automatic crack detection and classification techniques are essential for civil infrastructure. In our proposed approach, we introduce the Novel Crack Encroachment in Concrete Structures, classified using DCNN. Initially, the input image undergoes preprocessing with the novel ADNLMF (Anisotropic Diffusion Non-Local Mean Filtering) technique. These filters aim to reduce noise in the input images, with Anisotropic Diffusion preserving edge sharpness and Non-Local Mean denoising the images while retaining textures and features. The

collaborative ADNLMF effectively denoises the input image, preserving edges, textures, and features. The preprocessed image is then subjected to feature extraction using YOLO v3, a combination of YOLO v2, Darknet-53, and Residual networks, to detect structures as crack or non-crack. If a crack structure is detected, our research classifies it as a minor crack, major crack, Attention crack, or severe crack based on crack depth, calculated using the crack width transform technique. A DCNN-based classifier is employed to identify the type of cracks. Consequently, our innovative technique enhances accuracy, reduces network complexity, and saves time.

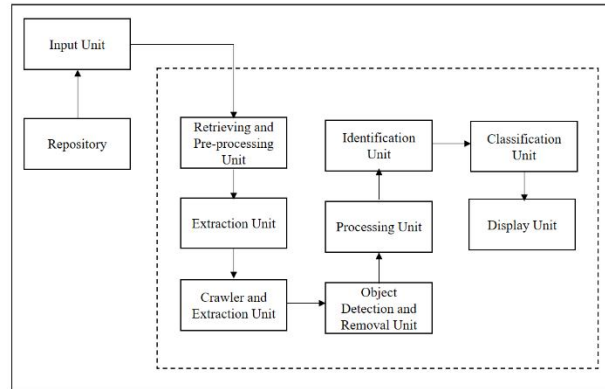


Figure 1 illustrates a block diagram of the proposed system for the detection and classification of irregularities in civil structures.

The proposed system discloses a method for the detection and classification of irregularities in a civil structure. Figure 1 includes a repository, an input unit, a retrieving and pre-processing unit, an extraction unit a crawler and extractor unit, an object detection and removal unit, a processing unit, an identification unit, a classification unit, and a display unit.

The repository is to store a dataset of civil structures, a set of predefined features, a set of classification rules, and a set of rules.

The input unit receives an image of at least one civil structure from an imaging device of a user. The imaging device is selected from a group consisting of a camera device, a scanner device, a computer, a laptop, a mobile device, and a USB device.

The retrieving and pre-processing unit retrieves the image from the input unit and is further configured to generate at least one pre-processed image using Anisotropic Diffusion Non-Local Mean Filtering (ADFMLF). The retrieving and pre-processing unit generates the pre-processed image by means of a de-noising, sharpening, normalizing, cropping, cleaning, transformation, reduction, quality assessment, and any combination thereof.

The extraction unit receives at least one pre-processed image and is further configured to extract at least one feature from the pre-processed image using Anisotropic Diffusion Non-Local Mean Filtering (ADFMLF). The set of features includes training dataset features, testing dataset features, and a validation dataset of said images.

The crawler and extractor unit crawl and match the extracted feature with the set of predefined features stored in the repository.

The object detection and removal unit receives the pre-processed images from the extraction unit and receives the matched extracted features from the crawler and extractor unit to detect one or more objects from the pre-processed images, the objects are selected from unwanted objects, overlapped objects, or both, and further configured to remove the objects and generate an enhanced pre-processed image. The object detection and removal unit generates the enhanced pre-processed image by means of machine learning, artificial intelligence, deep learning, convolution neural network, deep convolution neural network, and any combination thereof.

The processing unit receives the enhanced pre-processed image from the object detection and removal unit to generate a processed image. The processing unit generates the processed image with high quality for computation by means of machine learning, artificial intelligence, deep learning, convolution neural network, deep convolution neural network, and any combination thereof.

The identification unit receives the processed image from the processing unit to identify and mark at least one region in the processed image. The identification unit identifies at least one region of interest and marks a grid layout in the processed image.

The classification unit receives the processed image from the identification unit and the matched extracted features from the crawler and extractor unit, further detects at least one irregularity from the marked region, and classifies

at least one irregularity in the processed image in accordance with the set of classification rules from the repository and generate a notification for the at least one irregularity. The set of classification rules is selected from a group consisting of machine learning, artificial intelligence, deep learning, convolution neural network, deep convolution neural network, and any combination thereof. The classification unit detects and classifies irregularity, wherein irregularity is a type of crack irregularity selected from a group consisting of a beam, pillar, wall, surface, bridge, and building view. The display unit displays the notification of the irregularity.

III. RESULTS

Any irregularities in civil infrastructure are detected by the manual process which is carried out by the operator or by a team. Because of the involvement of human intervention, the process execution requires more time. This process does not provide regular synchronization of data and sometimes leads to false data. The main motivation is to detect the state irregularities in any images where traditional methods are very time-consuming. It is very difficult to identify the changes in civil structure but also those changes that are of interest, i.e. changes that reveal irregularities in civil infrastructures.

Figure 2A and Figure 2B depict the categories of sample images that consist of a Crack sample (Positive) and non-crack samples (Negative).

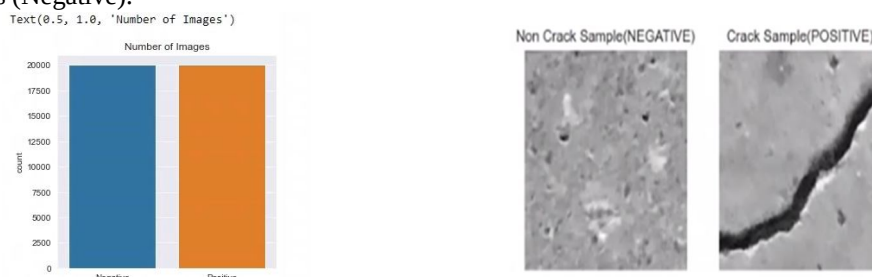


Figure 2A and Figure 2B illustrate a No crack sample and crack sample (Negative and Positive) of the images of the civil structure.

The above Figure 2A and Figure 2B describe the total number of images identified as Negative and Positive, wherein the 5991 images are identified as negative and 6009 images are identified as positive. Further following table shows the classification report of the said number of images as:

Classification Report:				
	precision	recall	f1-score	support
NEGATIVE	0.99	0.99	0.99	5991
POSITIVE	0.99	0.99	0.99	6009
accuracy			0.99	12000
macro avg	0.99	0.99	0.99	12000
weighted avg	0.99	0.99	0.99	12000

Following Figure 3A and Figure 3B describe the graph for classification report positive and classification report negative in accordance with the recall, f1-score and support.

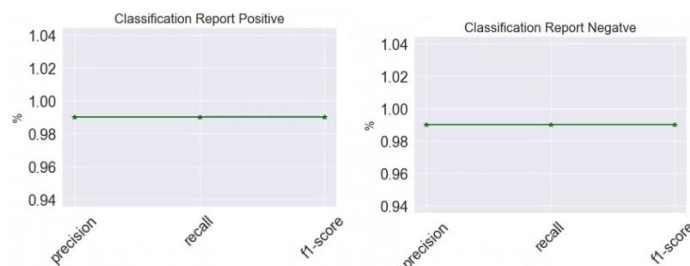


Figure 3A and Figure 3B illustrates graph of the classification report Positive/Negative of the images of the civil structure.

The confusion matrix provides a comprehensive summary of the performance of a predictive model. Comprising four key metrics true positive, true negative, false positive, and false negative—the confusion matrix allows for the evaluation of a model's accuracy, precision, recall, and overall effectiveness. True positive represents the

instances correctly predicted as positive, while true negative denotes the accurate prediction of negative instances. False positives are instances wrongly classified as positive, and false negatives are instances wrongly classified as negative. Following Figure 4 illustrates the confusion matrix describing the total number of images are identified as Negative and Positive.

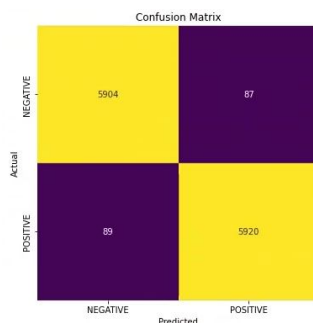


Figure 5 illustrates various crack samples of the images of the civil structure. The database encompasses a diverse collection of images capturing different types and degrees of cracks, ranging from surface-level fractures to more severe structural damage.

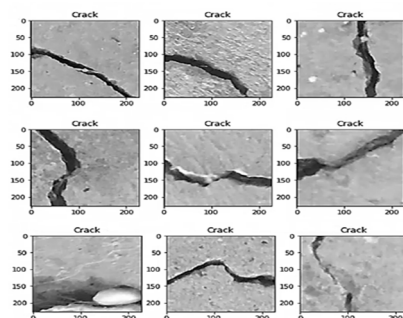


Figure 5 illustrates various crack samples of the images of the civil structure.

Figure 6A - Figure 6C illustrates a testing input image, a testing grayscale image, and a testing filtered image of the images of the civil structure. The set of features includes a training dataset features, a testing dataset features, and a validation dataset of said images. The pre-processed image by means of a de-noising, sharpening, normalizing, cropping, cleaning, transformation, reduction, quality assessment, and any combination thereof.

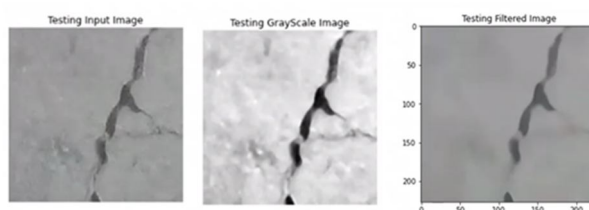


Figure 6A - Figure 6C illustrates a testing input image, a testing grayscale image, and a testing filtered image of the images of the civil structure.

Figure 7A - Figure 7C illustrates a processed image including the input image, filtered image, and crack detected. The enhanced pre-processed image by means of machine learning, artificial intelligence, deep learning, convolution neural network, deep convolution neural network, and any combination thereof. The processed image with high quality for computation by means of machine learning, artificial intelligence, deep learning, convolution neural network, deep convolution neural network, and any combination thereof.

The classification unit is configured to detect and classify irregularity, wherein irregularity is a type of crack irregularity selected from a group consisting of a beam, pillar, wall, surface, bridge, and building view. The set of classification rules is selected from a group consisting of machine learning, artificial intelligence, deep learning, convolution neural network, deep convolution neural network, and any combination thereof.

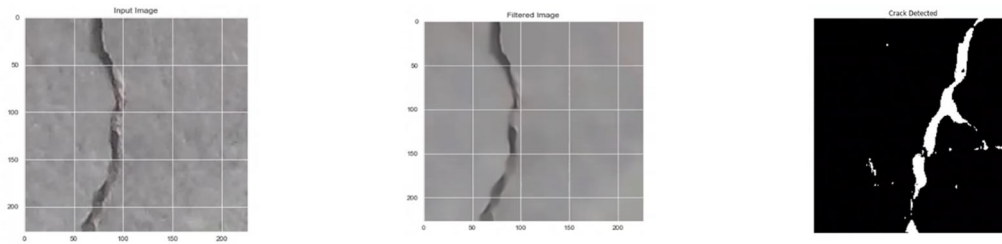


Figure 7A - Figure 7C illustrates a processed image including the input image, filtered image, and crack detected.

IV. ADVANTAGES

The proposed system disclosure described herein above has several technical advantages including, but not limited to, the realization of a system and a method for detection and classification of irregularities in civil structures that:

- **Enhanced Algorithm Development:** Investigate advanced machine learning algorithms and deep learning architectures to further enhance the accuracy and efficiency of crack detection and classification. Experiment with state-of-the-art neural network models and evaluate their performance against the proposed methodology.
- **Real-Time Implementation:** Focus on real-time implementation of the crack detection system. Develop strategies to optimize the algorithms for faster processing speeds, allowing for immediate detection and assessment of cracks in real-world scenarios.
- **Dataset Expansion and Diversity:** Expand the dataset used for training and testing the models. Include a diverse range of concrete structures, surface finishes, and environmental conditions to create a robust dataset. The diversity in data will enhance the model's adaptability to various real-world situations.
- **Transfer Learning and Fine-Tuning:** Explore transfer learning techniques by leveraging pre-trained models and fine-tuning them specifically for concrete crack detection. Transfer learning from general image datasets could provide a valuable starting point and improve the model's overall performance.
- **Edge Computing and IoT Integration:** Investigate the integration of crack detection algorithms with edge computing devices and Internet of Things (IoT) sensors. Implementing these algorithms directly on embedded systems can enable real-time analysis, reducing latency and improving the responsiveness of the system.
- **Robustness to Environmental Factors:** Enhance the system's robustness against environmental factors such as varying lighting conditions, shadows, and surface textures. Research methods to make the algorithm less sensitive to these factors, ensure accurate detection regardless of the external environment.
- **User-Friendly Interface:** Develop an intuitive and user-friendly interface for the crack detection system. A user interface with visualization tools and interactive features can facilitate the interpretation of results by engineers and inspectors, making the technology more accessible and practical.
- **Collaboration with Industry Experts:** Collaborate with civil engineers, construction professionals, and industry experts to gain valuable insights into the specific challenges faced during crack inspection. Incorporate domain knowledge to refine the algorithms and tailor them to the practical needs of the industry.
- **Long-Term Structural Health Monitoring:** Extend the system's capabilities for long-term structural health monitoring. Develop methods to track and analyze crack propagation over time, allowing for predictive maintenance and timely repairs to prevent structural failures.
- **Ethical and Social Implications:** Consider the ethical implications of automated crack detection systems, including issues related to privacy, data security, and the impact on employment in the inspection industry. Address these concerns to ensure the responsible and ethical deployment of the technology.

By addressing these areas of research, surface crack detection in concrete structures can witness significant advancements, leading to more accurate, efficient, and reliable methods for ensuring the structural integrity of civil constructions.

V. CONCLUSION

Irregularity detection in civil infrastructure is a critical task for maintaining public safety and property integrity. Traditional manual processes are time-consuming and prone to errors. This research introduces an innovative solution based on advanced image analysis and automation technologies to address these challenges. By providing a robust, efficient, and accurate method for detecting irregularities, this approach contributes to the early

identification and mitigation of potential threats to civil infrastructure. The dynamic set of classification rules is used to detect at least one irregularity from the region of civil structure images in a real-time, and further classify at least one irregularity in the processed image.

FUTURE SCOPE

Future research directions include the exploration of real-time monitoring using remote sensing technologies, the development of predictive maintenance models, and the integration of geographic information systems (GIS) for enhanced irregularity tracking and management. Additionally, ongoing advancements in AI and image analysis techniques will continue to refine and improve irregularity detection methods.

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